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(54) Title: UNCERTAINTY CONSTRAINED SUBSURFACE MODELING

(57) Abstract

A method, apparatus, and article of manufacture are provided that use measurement data to create a model of a subsurface area. The method includes creating an initial parameterized model having an initial estimate of model parameter uncertainties; considering measurement data from the subsurface area; updating the model and its associated uncertainty estimate; and repeating the considering and updating steps with additional measurement data. A computer–based apparatus and article of manufacture for implementing the method are also disclosed. The method, apparatus, and article of manufacture are particularly useful in assisting oil companies in making hydrocarbon reservoir data acquisition, drilling and field development decisions.

UNCERTAINTY CONSTRAINED SUBSURFACE MODELING

Related Applications

This application claims the benefit of U.S. Provisional
Application No. 60/119,821, filed February 12, 1999, and U.S.
Provisional Application No. 60/165,333, filed November 12,
1999.

Background of the Invention

This invention is related to subsurface modeling, and is more
particularly concerned with a parametric subsurface modeling
method, apparatus, and article of manufacture that use
uncertainty estimates of subsurface model parameters.

Subsurface models are typically created by geoscientists and
engineers to allow development strategies for the subsurface
area to be evaluated. Models of this type are commonly
created in connection with the development of hydrocarbon
reservoirs and mining sites, but they can also used during
drilling and related activities where the physical properties
of the subsurface area are important. This patent
application will focus on the process of creating and
updating a model of a subsurface hydrocarbon reservoir, but
it should be understood that this merely represents one
specific example of how a model of any subsurface area may be
created and updated.

Currently, hydrocarbon reservoir modeling is performed most
commonly in high-risk, high-profile situations. Typical
applications include discoveries in new areas, deepwater
exploration, fields in which production surprises or drilling
hazards have been encountered, fields in which secondary and
tertiary recovery activities are planned, and fields which
are being considered for sale or abandonment. The failure to
adequately model hydrocarbon reservoirs can have numerous
adverse financial consequences, including inaccurate reserve

calculations, drilling or completion problems, improper production facility sizing, and suboptimal well placement.

The general problem addressed by this invention is how to construct a model of a subsurface area that is in agreement with multiple sets of measurement data. A model that is in agreement with all of the measurement data obtained from the reservoir can help address many of the problems noted above. By 'reservoir model' we mean a quantitative parameterized representation of the subsurface in terms of geometries and material properties. The geometrical model parameters will typically identify geological boundaries, such as contacts between different geologic layers, faults, or fluid/fluid interfaces. The material model parameters will typically identify properties of distributed subsurface materials, such as seismic wave velocities, porosities, permeabilities, fluid saturations, densities, fluid pressures, or temperatures.

By 'agreement' we mean that the data predicted from the reservoir model fit measurements made on the actual reservoir (seismic data, drilling data, well logging data, well test data, production history data, permanent monitoring data, ground penetrating radar data, gravity measurements, etc.). Virtually all types of measurement data have quantifiable uncertainties and the reservoir model agrees with the measurement data when the difference between data predicted by the reservoir model and measurement data obtained from the reservoir is less than this inherent measurement uncertainty. While creating a reservoir model that fits one data set is a relatively straightforward task, it is much more difficult to ensure that the model is in agreement with multiple data sets, particularly if the data sets consist of different types of data.

A reservoir model, however, is nonunique even if it is made to fit a variety of data, because different values of

material properties and geometries within the model can
result in similar predicted measurement values. In other
words, the reservoir model has inherent uncertainties: each
of the numerical parameters in the reservoir model (e.g.,
values of material properties within a layer) can take a
range of values while the model remains in agreement with the
data. This range in parameter values is the uncertainty
associated with the reservoir model. The invention described
herein is a method to integrate information from multiple
measurements and to obtain a reservoir model with
quantitative uncertainties in the model parameters. A model
of the reservoir that fits the data and has quantified
uncertainties can be used to assess the risk inherent in
reservoir development decisions (e.g., deciding on the
location of additional wells) and to demonstrate the value of
additional measurements by showing how these measurements
decrease uncertainties in model parameters of interest (e.g.,
the location of a drilling target or hazard).

A Shared Earth Model (SEM) is a geometrical and material
property model of a subsurface area. The model is 'shared' in
the sense that it integrates the work of several experts
(geologists, geophysicists, well log analysts, reservoir
engineers, etc.) who use information from a variety of
measurements and interact with the model through different
application programs. Ideally, the SEM contains all
available information about a reservoir and thus is the basis
to make forecasts and plan future actions.

Yet, in any practical case, the information in the
measurements is not sufficient to uniquely constrain the
parameters (geometries and material properties) of a SEM. As
noted above, any SEM has an associated uncertainty, defined
here as the range that model parameters can take while
fitting available measurements.

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The invention has two primary aspects. The first aspect is a
method to quantify and update model parameter uncertainties
based on available measurements. One embodiment of this
method is based on Bayes' rule, with SEM uncertainty
quantified by a posterior probability density function (PDF)
of the model parameters, conditioned on the measurements used
to constrain the model. This posterior PDF may be
approximated by a multivariate normal distribution, which is
fully described by the posterior mean and covariance matrix
of the SEM parameters. Alternatively, one can use a Monte
Carlo method to obtain a sample of models drawn from the
posterior PDF. This sample of models spans the uncertainty
implied by the measurements.

The second aspect is how such a measure of uncertainty acts
as a 'memory' of the SEM and can be used for consistent model
updating. Quantified uncertainties provide a mechanism to
ensure that updates of the SEM based on new data (e.g., well
data) are consistent with information provided by data
examined previously (e.g., surface seismic data). In
particular, we show through a simple example how the effects
of a local update of the model can be propagated using the
posterior covariance matrix of the SEM parameters. We also
show how to update a sample of models obtained by the Monte
Carlo method to include new information.

The ideal of a SEM is that all specialists should be able to
interact with a common geometry and material property model
of the reservoir, incorporating changes into the model using
measurements from their own domain of expertise, while
maintaining model consistency with previous measurements.
This SEM representation would always be consistent with all
available information and should be easy to update as soon as
new measurements become available (e.g., from additional
wells). Model building would not be a task done episodically,
but instead the reservoir model would evolve incrementally as

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more and more information becomes available during
development and production.

While acquiring more measurements can reduce uncertainty, it
is important to weigh the cost of data acquisition against
the benefits of reducing uncertainty. This can be done using
the tools of decision theory, where different decisions are
compared given their associated gains/costs and current
uncertainties. A consistent quantification of uncertainties
can assist oil companies in making data acquisition,
drilling, or development decisions.

Currently, reservoir models are simply modified to fit new
data and confirming that the modification is not inconsistent
with the previously obtained measurement data is left up to
the discretion of the user. The reservoir model may be the
result of years of effort and may incorporate measurement
data from a wide variety of sources. A user will often only
confirm that the change made is not inconsistent with the
measurement data within his or her area of expertise (a well
log analyst may confirm, for instance, that the change made
is consistent with the other well logging data, but may not
determine whether the change has introduced an inconsistency
with the seismic or geologic data from the area). Many
reservoir simulations rely heavily on production data from
wells and only four types of geological or geophysical
reservoir information: structure of the top of the reservoir,
reservoir thickness, porosity, and the ratio of net pay to
gross pay. These maps are often constructed from seismic and
well log data alone. Incorporating all available data, such
as core analyses, seismic-guided reservoir property
distributions and fluid analyses, and making certain that the
reservoir model is consistent with these different types of
data is a cost-effective way to stregthen and validate
reservoir models across disciplines.

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An iterative method to obtain a model that fits some of the
data has been described by George W. Celniker in commonly-
assigned U.S. Patent No. 5,905,657, issued March 18, 1999 and
incorporated herein by reference. In the Celniker method,
the user examines the difference between predicted and
measured data, modifies the model attempting to decrease this
difference, and repeats the procedure until the fit is
satisfactory. This procedure may be adequate if all data sets
are considered simultaneously, which may be impractical for
diverse and large data sets. If instead the model is modified
to fit each of the N data sets in turn (say, from $d^{(1)}$ to $d^{(N)}$
), there is no guarantee that the modifications made to fit
the ith data set $d^{(i)}$ do not make the model inconsistent with
any of the data sets examined previously ($d^{(1)}$, $d^{(2)}$, ...,
$d^{(i-1)}$). The model can be assured to be consistent with all
data sets only by repeating the comparisons with each data
set. Also, if a new data set is acquired and the model is
modified to fit it, all other data sets must be examined
again to ensure consistency. These repeated checks can make
the method time-consuming and inefficient in practice.
Moreover, an iterative comparison of predicted and measured
data does not by itself quantify the uncertainty in the model
(defined, *e.g.*, as the range that the model parameters can
span while still fitting the measured data).

Brief Summary of the Invention

The invention comprises a parametric subsurface modeling
method, apparatus, and article of manufacture that use
measurement data to create a model of a subsurface area. The
method includes the steps of: creating a parameterized model
having an initial estimate of model parameter uncertainties;
considering measurement data from the subsurface area;
updating the model to fit the measurement data, the updated

model having an updated estimate of model parameter
uncertainties; and repeating the considering and updating
steps with additional measurement data. A computer-based
apparatus and article of manufacture for implementing the
method are also disclosed. The method, apparatus, and
article of manufacture are particularly useful in assisting
oil companies in making hydrocarbon reservoir data
acquisition and field development decisions. Features of the
invention, preferred embodiments and variants thereof,
possible applications and their advantages will become
appreciated and understood by those skilled in the art from
the following detailed description and drawings.

Brief Description of the Drawings

FIG. 1 is a flowchart showing steps associated with the
present method, apparatus, and article of manufacture;

FIG. 2 is a schematic illustration of computer hardware
associated with the apparatus and article of manufacture;

FIG. 3 is a related group of diagrams used to describe a
first embodiment of the inventive method;

FIG. 4 is a related group of diagrams used to describe the
first embodiment of the inventive method;

FIG. 5 is a related group of diagrams used to describe a
second embodiment of the inventive method.

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Detailed Description of the Invention

Figure 1 shows several steps associated with the present
method, apparatus and article of manufacture and provides a
general overview of the invention.   In the Create Subsurface
Model Step 10, a parameterized model of a subsurface area is
created using initial reservoir information 12 and/or initial
measurement data 14.   The initial parameterized model will
have an associated initial estimate of model parameter
uncertainties.

The model of the subsurface area will typically have
geometrical model parameters representing geological
boundaries and material parameters representing properties of
distributed subsurface materials.   The model of the
subsurface area may be, for instance, a layered medium
representing a layered earth with material properties that
are constant or variable within each layer; a geocellular
model having material property values defined on a regular or
irregular three-dimensional grid; or may be a geometry-based
model having material property values defined on a plurality
of discrete geometrical sub-regions within the subsurface
area.

The initial information may consist of prior knowledge of the
spatial distribution of material properties in the
subsurface, e.g., the increase of seismic velocity with
depth.   The initial information may come from physical laws
or measurements made in subsurface areas other than the one
being modeled.   The initial measurement data may consist of
seismic data, drilling data, well logging data, well test
data, production history data, permanent monitoring data,
ground penetrating radar data, gravity measurements, etc. or
various combinations of these types of data.

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The initial estimate of model parameter uncertainties will typically consist of probability density functions, and preferably consist of multivariate normal/lognormal probability density functions definable by mean vectors and covariance matrices.

In the Consider Measurement Data Step 16, Measurement Data 18 that provides information regarding the subsurface model parameters is examined. In certain cases, the Measurement Data 18 will provide information that may be compared directly to one or more of the subsurface model parameters. Well logging data may, for instance, give direct measurements of the thickness or the compressional seismic wave velocity of a given geologic layer. In other cases, a Prediction Algorithm 20 will be used to compute data predicted by the model that can be compared to Measurement Data 18, because the Measurement Data 18 only indirectly measures one or more of the subsurface model parameter values. Identify Inconsistencies 22 is used to flag those occasions when the Measurement Data 18 being considered is inconsistent with the model and its associated uncertainty estimate.

In the Update Model and Uncertainty Estimate Step 24, the model is updated to fit the Measurement Data 18 (typically within the model uncertainty constraints). The estimate of model parameter uncertainties is updated as well using the Measurement Data 18. The Consider Measurement Data Step 16, may for instance, produce a likelihood function that is combined with the initial estimate of model parameter uncertainties to produce both the updated parameterized model as well as the updated estimate of model parameter uncertainties. For example, the mean and covariance matrix of the updated estimate of model parameter uncertainties may be computed using deterministic optimization. Alternatively, one may use Monte Carlo sampling to obtain a number of models that are consistent with the Measurement Data 18. These

samples may be used to compute the mean and covariance matrix
of the updated model parameter uncertainties.

The Consider Measurement Data Step 16 and the Update Model
and Uncertainty Estimate Step 24 are repeated for Additional
Measurement Data 26 to produce a further updated
parameterized model having a further updated estimate of
model parameter uncertainties.

The Measurement Data 18 and the Additional Measurement Data
26 may, for instance, consist of different types of data,
such as seismic data and well logging data. The Measurement
Data 18 and the Additional Measurement Data 26 may,
alternatively, consist of the same type of data that has been
acquired from the subsurface area at different times to
measure changes in reservoir, such as time-lapse/4D surface
seismic data.

At least two additional alternative methods for managing the
model update process are possible. In some cases, it may be
preferable to allow the model parameters to be changed only
when the change is consistent with the earlier estimate of
model parameter uncertainties. In other cases, Identify
Inconsistencies 22 may be used to identify changes in the
model parameters that appear to be inconsistent with the
initial estimate of model parameter uncertainties derived
from the previously considered measurement data. This is
generally an indication that model assumptions and data
quality assumptions need to be re-examined.

The Consider Measurement Data Step 16 and the Update Model
and Uncertainty Estimate Step 24 may be repeated as desired
using Additional Measurement Data 26 to further update the
model of the subsurface area and its associated estimate of
model parameter uncertainties. This may be repeated, for

instance, whenever a new set of Additional Measurement Data 26 from the subsurface area becomes available.

Figure 2 schematically illustrates computer hardware that may be used to implement the inventive method. Computer 30 has a media reading device, such as floppy disk device 32, a CD-ROM Reader or a ZIP drive. The media reading device may also be capable of recording the output of the program the computer 30 is running. A user of the computer 30 may enter commands using a user input device, such as a keyboard 34 or a mouse, may view output of the program code on a visual display device, such as monitor 36, and may make hardcopies of output using an output device, such as printer 38. When properly configured, computer 30 (and its associated peripheral devices) is an apparatus for creating a model of a subsurface area in accordance with the present invention. Computer media, such as floppy disk 40, a CD-ROM or a ZIP disk, may have computer readable program code that allows the computer 42 to create a model of a subsurface area in accordance with the inventive method.

A preferred embodiment of the inventive method will now be described in substantially more detail. The inventive method addresses two primary issues: how to quantify uncertainties in a SEM given measurements and how to use these uncertainties to ensure consistent model updating. The latter is an important issue because in a SEM environment one should be able to continuously update the model; however, model updates based on a set of new data must be consistent with the information provided by data examined previously. We will now show how to generally address these issues using two simple examples where model uncertainties are calculated and updated using seismic and well data.

The first example will be used to illustrate the quantification of uncertainty in a multivariate normal

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distribution and consistent model updating environment and will use a simple two-dimensional SEM containing three layers (see Figure 3, diagram 42). This model has seven parameters: the thicknesses h_i of the two top layers at two locations define the SEM geometry, and three compressional wave velocities V_{pi} are material properties. We use layer thicknesses here rather than the absolute depths of horizons because thicknesses are better suited for optimization. Uncertainties in layer thickness can be easily transformed to uncertainties in absolute depths.

We suppose that at the outset there are measured surface seismic data in the form of four traces recorded at different locations (Figure 3, diagram 44). These four traces were computed by convolving a 50-Hz seismic wavelet with the normal-incidence reflection coefficients of a 'true' model. The layer thicknesses and velocities in the true model are in parentheses in diagram 42. The densities needed to compute the reflection coefficients were obtained using Gardner's law, which gives rock density as a function of compressional wave velocity. To make the data more realistic, we added band-limited noise for a signal-to-noise ratio of 10.

The second example, see Figure 5, consists of a layered model and will be used to illustrate the quantification of uncertainty using a Monte Carlo method. The data consists of a single seismic reflection trace, and the uncertainty quantification problem is to infer how much variability in the layered medium parameters is consistent with the data given an assumed signal-to-noise ratio.

Quantifying SEM uncertainty from measurements

To quantify uncertainty, we use the Bayesian approach widely adopted in the statistical and geophysical inversion literature. Denote the SEM parameters with a vector $\mathbf{m} = [m_1,$

$m_2, \ldots, m_M]^T$ and the seismic data with a vector $\mathbf{d} = [d_1, d_2, \ldots, d_N]^T$ (we use bold lowercase letters for vectors and bold uppercase letters for matrices; the superscript T denotes the transpose). The final uncertainty is quantified by a posterior probability density function (PDF) of the model parameters in $\mathbf{m}$, which can be obtained from Bayes' rule as the product of a prior PDF and a likelihood function (Figure 4, diagrams 60-74):

$$p(\mathbf{m} \mid \mathbf{d}, I) \; \alpha \; p(\mathbf{m} \mid I) \; L(\mathbf{m} \mid \mathbf{d}, I),$$

where $p(\mathbf{m} \mid \mathbf{d}, I)$ is the posterior PDF (the PDF of the SEM parameters $\mathbf{m}$ given the data $\mathbf{d}$, $p(\mathbf{m} \mid I)$ is the prior PDF, $L(\mathbf{m} \mid \mathbf{d}, I)$ is the likelihood function, and α denotes proportionality. It might seem an impossible task to write an expression for the model PDF given the poor state of knowledge of the reservoir. This is possible by making the PDFs conditional on some prior information I, which includes the parametric form of the model, the noise model, and the accuracy of the physics and simulators used to predict the measurements for a given value of the model parameters.

The prior PDF quantifies what is known about the model parameters from the prior information only, i.e., independently of the information provided by the data. For the initial SEM of diagram 42, we used as a prior PDF a uniform distribution for the layer thicknesses (between a minimum of 1 m and a maximum of 400 m) and a normal distribution for the compressional wave velocities (with a mean of 2500 m/s, a standard deviation of 500 m/s, a minimum of 1500 m/s and a maximum of 5000 m/s). Prior uncertainties in the SEM parameters were also assumed to be independent, so that the prior PDF of all parameters is just the product of the prior PDFs of each:

$$p(\mathbf{m} \mid I) = p(m_1 \mid I) \, p(m_2 \mid I) \, \ldots \, p(m_7 \mid I)$$

This prior PDF represents an initial state of information where the layer thicknesses are unknown, while the prior PDF of the velocities reflects what is expected for sedimentary rocks.

Information provided by measurements is quantified by the likelihood function, which is formally the probability of observing the data **d** when the model parameters equal **m**. For the data of diagram 44, we assumed from prior information that the measured data contained measurement errors that were normally distributed with a standard deviation σ. The likelihood function is then

$$L(\mathbf{m} \mid \mathbf{d}, I) \; \alpha \; \exp\{-[1/(2\sigma^2)] \, [\mathbf{d} - \mathbf{g}(\mathbf{m})]^{\mathsf{T}} \, [\mathbf{d} - \mathbf{g}(\mathbf{m})]\},$$

where **g**(**m**) is a forward modeling (i.e. simulation, prediction) operator that returns the value of the data calculated for a given value of the SEM parameters. In our case, this operator gives the data computed by convolving a seismic wavelet (assumed known) with the reflection coefficient sequence corresponding to the parameters in the SEM. The combination of the prior and likelihood tells us what we know about the model parameters a *posteriori*.

Diagrams 60 through 74 show how to update a posterior PDF when new data become available. In the first row, a posterior PDF is obtained when there are only data $\mathbf{d}^{[1]}$. When more data become available, indicated by $\mathbf{d}^{[2]}$, the posterior PDF as constrained by all the data can be obtained by applying Bayes' rule again while using as the prior PDF the posterior obtained previously. This simple update can be done if errors in the data $\mathbf{d}^{[1]}$ and $\mathbf{d}^{[2]}$ are independent, which is a reasonable assumption for data of different types.

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Diagrams 60 through 74 also illustrate how uncertainty can be quantified. At any stage in the process, the posterior PDF can be approximated by a multivariate normal distribution as in

$$p(\mathbf{m} \mid \mathbf{d}, I) = \text{const. } \exp[-(1/2) \, (\mathbf{m} - \mu)^T \, \mathbf{C}^{-1} \, (\mathbf{m} - \mu)].$$

In this approximation, the posterior PDF is fully described by the mean value of the model parameters μ and by the covariance matrix $\mathbf{C}$. The mean (indicated by the white triangles 62, 68, and 76 in diagrams 60, 66, and 74) gives a most probable, 'best' value of the SEM parameters; the covariance matrix defines an ellipsoid in parameter space describing the shape of the posterior PDF (the ellipses 70 and 78 in diagrams 66 and 74), an indication of model parameter uncertainty.

A general practical recipe to evaluate μ and $\mathbf{C}$ uses nonlinear optimization of an objective function

$$\Phi(\mathbf{m}) = \log p(\mathbf{m} \mid \mathbf{d}, I).$$

A generic optimizer (e.g., quasi-Newton) can be used to find the maximum of the objective function, and the value of $\mathbf{m}$ at the maximum can be taken to correspond to the posterior mean μ. The posterior covariance matrix $\mathbf{C}$ can be computed as the inverse of the Hessian matrix (the matrix of second derivatives) of the objective function evaluated by finite differences around μ.

The result of applying the nonlinear optimization procedure to the SEM and data of diagrams 42 and 44 is illustrated in diagrams 46 and 48. While the seismic data predicted by the

best values of the SEM match closely the measured data, there
are large uncertainties in the layer thicknesses and wave
velocity in the top layer. This illustrates the fundamental
non-uniqueness of time-depth conversion: increasing
simultaneously thickness and wave velocity in the top layer
does not change the travel time of the reflection. The data
do not constrain well the combination of layer thickness and
wave velocity, and this uncertainty has been captured in the
posterior covariance.

Generic optimization algorithms are typically 'local', in the
sense that they find a maximum by moving toward higher values
of the objective function from a starting point. Therefore,
if the objective function has multiple maxima (as often is
the case for band-limited seismic data), the optimizer may
converge to a meaningless local maximum. If there are
multiple local maxima, these optimizers will converge to the
global maximum only if they start from a value of m that is
close to (in the sense of being downhill from) that maximum.
For these optimizers to be useful in practice, the user
should have the capability to search for a reasonably good
starting point by trial-and-error interactions with the SEM.

The uncertainties computed from the Hessian matrix are also
'local' because they are obtained from the local curvature of
the objective function near its maximum. The uncertainties
computed in this fashion will be accurate only if the
objective function is well approximated by a quadratic, *i.e.*,
if the posterior PDF is well approximated by a multivariate
normal distribution. An alternative is to use a Monte Carlo
sampling strategy where values of the model parameter vector
m are sampled from the posterior PDF. While uncertainties
computed from the Hessian matrix are likely to be useful in
many instances, there may be cases where a Monte Carlo
approach is necessary to obtain a sufficiently accurate
uncertainty quantification.

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The Monte Carlo approach is illustrated in the example of
Figure 5. The data **d** 86 are seismic reflection data, and the
model parameters in the vector **m** are

$$\mathbf{m} = (n, \ t, \ v),$$

where n is the number of layers, **t** is a vector of travel
times to the layer interfaces, and **v** is a vector of
compressional wave velocities or acoustic impedances in each
of the layers.

The three profiles 88 are obtained by sampling the posterior
PDF of the parameters using a Monte Carlo algorithm. In
practice, this can be done in two steps: first obtain a
sample of layered media in travel time from the posterior
PDF, and then convert each of the sampled layered media from
travel time to depth starting from a travel time-depth tie (a
point where the travel time and depth are known or have been
measured). The image 90 is obtained by superimposing a large
number of layered media sampled from the posterior PDF and
gives an image of the uncertainty in compressional wave
velocity with depth for a given travel time-depth tie.

A method that may be used to obtain a sample from the
posterior PDF is the Metropolis-Hastings algorithm. Each step
of the algorithm consists of choosing a "candidate" layered
medium by perturbing the current one (e.g., by adding a
layer, deleting a layer, or changing the travel time to a
layer interface). This amounts to choosing a candidate
parameter vector **m'** from a "candidate PDF" $q(\mathbf{m'}|\mathbf{m})$, that is
the distribution of possible candidates given the current
value **m** of the parameter vector. In the Metropolis-Hastings
algorithm, the candidate is accepted with probability

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alpha = min {1, [$p(m'|d, I)/p(m|d, I)$] [$q(m|m')/q(m'|m)$]}.

It can be shown that a sequence of models obtained with this simple algorithm will eventually sample the posterior PDF $p(m|d, I)$. Once a sample of layered media is obtained, it is easy to convert travel time to depth by starting from a known travel time-depth tie and computing the thickness of the i-th layer h_i as

$$h_i = deltat_i \; v_i /2,$$

where $deltat_i$ is the thickness of the i-th layer in travel time and v_i is the velocity of the i-th layer.

The Monte Carlo approach provides a more detailed and accurate quantification of uncertainty compared to the multivariate normal distribution method described above. A Monte Carlo approach such as that shown in Figure 5 accounts for the possibility of having different number of layers in the reservoir model and captures the uncertainty of posterior PDFs that are not well approximated by a normal distribution. For example, Figure 5 shows that the PDF of compressional wave velocity at a given depth may be multimodal. If a description of uncertainty in terms of a multivariate normal distribution is needed, however, it is easy to compute a posterior mean μ and a posterior covariance matrix C from the result of Monte Carlo sampling.

Using SEM Uncertainty for Consistent Model Updating

The uncertainties computed and displayed in diagram 46 are obviously useful in that they quantify how well the seismic data constrain each parameter of the SEM. Uncertainties also provide a 'memory' to the model: if information on the covariance matrix were stored with the model, it would

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effectively remember the constraints placed by all the data
types that the model was tested against.

The most general way to update the model and its uncertainty
when new data become available is illustrated in diagrams 60
through 74, and consists of a repeated application of Bayes'
rule. In this section we describe two methods that can be
used to quickly accomplish model updating and that can be
used when new data becomes available (e.g., from a well) to
update a SEM whose uncertainty has been quantified using a
multivariate normal distribution or the Monte Carlo approach.

An important use of quantified uncertainty is in propagating
model updates to ensure consistency of the SEM with
previously examined data. We illustrate the first method for
consistent model updating, which is applicable when the
uncertainty is quantified in a multivariate normal PDF form,
by considering what happens when new information from a well
becomes available. The simplest update is illustrated in
diagrams 50 and 52: when observations from a well drilled at
the left edge of the SEM show that the thicknesses of the top
two layers are 200 m and 20 m, the model is simply updated to
reflect the new information.

If layer thicknesses in the model of diagrams 46 and 48 are
changed to reflect values observed at a well without changing
any other SEM parameters, the predicted seismic data do not
match anymore the measured data. To ensure consistency, one
would have to match the model to the seismic data again after
the update.

In the case of time-depth conversion this is not unrealistic,
and the consequences of changes in layer thicknesses can be
calculated in a straightforward way. But in the general case
where a SEM has been constrained by a variety of data, there

is no obvious way to compute how the effects of a local
update should be propagated to maintain consistency.

We now describe a simple mechanism where quantified
uncertainties are used to propagate the effects of a local
model update to ensure consistency of a SEM with data
examined previously. The mechanism uses the transmission of
information provided by Bayes' rule (diagrams 60 through 74)
and is illustrated in diagram 80. After considering only the
seismic data, diagram 80 shows as a shaded ellipse the
posterior PDF of the compressional wave velocity V_p and
thickness h of a layer; the best value of V_p and h is shown
as a white triangle 82. Suppose now that, as shown in
diagrams 50 and 52, new information from a well becomes
available and it is now known that the layer thickness must
be within a narrow interval, indicated by the narrow cross-
hatched rectangle in chart 80. The best value for V_p and h
given the well data is now located at dot 84, which is the
point within the narrow rectangle where the posterior PDF
given the seismic data only is greatest. Note that the
information from the seismic data specifies that if the best
value of the layer thickness changes, the best value of the
layer wave velocity must change as well.

At the limit where the layer thickness is fixed with absolute
certainty by the well observations (*i.e.*, the rectangle in
chart 80 shrinks to a vertical line), the operation
illustrated in chart 80 is the calculation of the conditional
mean of V_p for a given value of h. In the general case where
one wants to compute the mean of some model parameters
conditional on other model parameters that have been updated,
this calculation is straightforward. Start by rearranging the
vector of SEM parameters **m** into two vectors

$$m = \begin{bmatrix} m_1 \\ m_2 \end{bmatrix},$$

where the vector m_1 contains the parameters whose conditional mean is to be computed, and the vector m_2 contains the parameters that are fixed. In the example of Figure 3, diagrams 50 and 52, m_2 would contain the two layer thicknesses constrained by the well observations and m_1 the two other layer thicknesses and the three wave velocities. After considering some data (seismic data in the example of Figure 3, diagrams 50 and 52), suppose we have a multivariate normal posterior PDF for m with mean μ and covariance C. Rearrange the mean vector as done for m in two vectors μ_1 and μ_2 and the covariance matrix as

$$C = \begin{bmatrix} C_{11} & C_{12} \\ C_{12}^T & C_{22} \end{bmatrix}.$$

It can be shown that the mean of the parameters in m_1 conditional on the other parameters having a value m_2 is

$$\mu_1 + C_{12} \, C_{22}^{-1} \, (m_2 - \mu_2)$$

and the conditional covariance of the parameters in m_1 is

$$C_{11} - C_{12} \, C_{22}^{-1} \, C_{12}^T.$$

This approach can be easily applied to the example of Figure 3, diagrams 50 and 52. Figure 3, diagrams 54 and 56 show the result of adding the well data using a 'consistent' model update, i.e., computing the mean and covariance of the seismically-defined SEM parameters conditional on the two values of thickness observed at the well. In simple terms,

this is a consistent update because it uses the information
provided by the seismic data to propagate the effects of a
local model update done on the basis of well data to other
model parameters in order to preserve consistency with the
seismic data. For example, the seismic data imply that if the
thickness of the top layer is modified, the wave velocity
must change as well. The conditional value computed from the
uncertainty for the top layer wave velocity is 1997 m/s,
which is very close to the true value (2000 m/s; see diagrams
42 and 54).

Diagrams 54 and 56 also show that the data predicted by the
updated SEM match the measurements well, in contrast with the
SEM of diagrams 50 and 52. It is important to stress that
this close match has not been achieved by comparing the SEM
predictions with the seismic data again after the well data
were incorporated in the model. The good fit to the
measurements is simply a result of using the posterior PDF to
compute a consistent model update. This is the key advantage
of quantifying uncertainties; at first approximation, *the
effects of any update to the SEM can be propagated using the
posterior uncertainties without needing to re-examine all
data previously incorporated into the model.* The posterior
uncertainties are a 'memory' mechanism that allows the SEM to
remember how closely data constrain its geometries and
material property distributions.

The limitations of this mechanism follow from the limitations
on the quantification of uncertainty noted in the previous
section. If the multivariate normal representation we use
here does not approximate the posterior PDF closely, the
computed consistent update will suffer. In our example, it is
clear that while the seismic data predicted by the
consistently updated SEM are close to the measurements, the
fit may be improved (compare diagrams 54 and 56 with diagrams
46 and 48). Also, some uncertainties are smaller than they

should be; for example, the uncertainty in the thickness of
the second layer should be greater than 0.8 m.

On the other hand, the updated model should be close to the
best value and thus an automated optimization applied at this
stage should have a good chance of succeeding. Starting from
the model of diagrams 50 and 52, an optimization converges to
a meaningless local maximum; if one starts instead from the
consistently updated model of diagrams 54 and 56, the
optimization quickly converges to a best model with an
improved fit to the seismic data. Once the best model is
found, the posterior covariance matrix may be evaluated again
for more accurate uncertainty quantification.

In the previous section we also described a Monte Carlo
approach to quantify uncertainty. If the model uncertainty
is quantified in a multivariate normal distribution whose
mean μ and covariance matrix C are evaluated from the result
of Monte Carlo sampling, the consistent update method we have
illustrated above can be used to compute a quick update, i.e.
without requiring the Monte Carlo sampling process to be
repeated. We now illustrate a second method that uses
additional information to directly update the sample from the
posterior PDF obtained by a Monte Carlo method.

The method we describe can be applied when the additional
information that becomes available directly controls the
properties of the posterior PDF sample. In the example of
Figure 5, diagrams 86-90, a Monte Carlo method was used to
obtain a sample from the posterior PDF of the thicknesses and
compressional wave velocities in a layered medium. Because
the seismic reflection data are in travel time, obtaining a
layered medium description in depth requires having a travel
time-depth tie, that is, having a point where the absolute
depth and the corresponding travel time are known or
measured. This travel time-depth tie may be the Earth's

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surface, where depth and travel time are zero.   For offshore
reservoirs, the travel time-depth tie may be at the sea
bottom.   If the seismic data were acquired using receivers or
sources in a borehole, the travel time-depth tie may be
obtained at the depth of a receiver/source in the borehole.
As will be clear to those skilled in the art, the uncertainty
in the depth of a layer as determined from seismic reflection
data is greater the farther away the layer is from the
deepest travel time-depth tie.   This is because depth is the
sum of layer thicknesses starting from the deepest travel
time-depth tie; the uncertainty in depth is the cumulative
uncertainty of the layer thicknesses.

Diagrams 92 and 94 illustrate our method of updating a
layered model and its uncertainties as new information on
travel time-depth ties becomes available.   Diagram 92 shows
the results of Monte Carlo sampling obtained for a relatively
shallow travel time-depth tie (e.g. the Earth's surface, the
sea floor, the depth of a seismic receiver/source in a
borehole).   The results are presented in the form of a
posterior image (as in diagram 90) computed by superimposing
all the layered media sampled by the Monte Carlo method.   As
noted in the previous section, in practice the Monte Carlo
sampling obtains a sample of layered media in travel time,
rather than depth; each of these layered media is then
converted to depth using a known/measured travel time-depth
tie.

Diagram 94 illustrates how the uncertainty in depth changes
if a deeper travel time-depth tie is measured.   This
additional travel time-depth tie will typically be provided
by a seismic receiver/source placed in a borehole, and it
could be acquired during or after drilling the well.   Diagram
94 shows how the uncertainty in deep layers is reduced by
using the deeper travel time-depth tie.   It should be
stressed that the application of this method does not require

sampling the posterior PDF again, but simply using the same sample of layered media in travel time obtained earlier while recomputing the travel time to depth conversion for the additional, deeper travel time-depth tie. This reduction in uncertainty can be extremely important in making decisions during the drilling of a well (e.g., on determining the depth of zones that have anomalous pore pressures and are drilling hazards).

Uncertainty quantification and consistent model updating can improve significantly the efficiency of constructing and modifying a SEM. Because industry-standard interpretation workflows don't account for uncertainty, model consistency is maintained by making elements of the model 'rigid' as the interpretation progresses down the workflow. The term 'rigid' means here that once a domain expert has set the optimal values for parameters under his control (*e.g.,* a geophysicist interpreting the model framework), these values are not changed by later experts (*e.g.,* a reservoir engineer) for fear that the model will no longer be consistent with the previous data. For example, once the model framework is fixed, the reservoir engineer is only left flow parameters to adjust during history matching. Explicitly accounting for uncertainty would allow that same reservoir engineer to adjust all parameters of the model within their acceptable ranges to obtain the best history match. The remaining uncertainty in the model then provides input to decision-making tools which, for example, can be used to estimate a PDF of the net present value of a reservoir. Thus, uncertainty quantification allows us to approach the ideal of a SEM that is constrained by as many data as possible, can be easily updated, and ties directly into decision-making tools.

The foregoing description of the preferred and alternate embodiments of the present invention have been presented for purposes of illustration and description. It is not intended

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to be exhaustive or limit the invention to the precise
examples described. Many modifications and variations will
be apparent to those skilled in the art. The embodiments
were chosen and described in order to best explain the
principles of the invention and its practical application,
thereby enabling others skilled in the art to understand the
invention for various embodiments and with various
modifications as are suited to the particular use
contemplated. It is intended that the scope of the invention
be defined by the accompanying claims and their equivalents.

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CLAIMS

We claim:

1.   A method of using measurement data to create a model of
a subsurface area comprising the steps of:

        creating a parameterized model of the subsurface
area having an initial estimate of model parameter
uncertainties;

        considering measurement data from the subsurface
area;

        updating said parameterized model to fit said
measurement data, said updated parameterized model having an
updated estimate of model parameter uncertainties; and

        repeating said considering and updating steps with
additional measurement data to produce a further updated
parameterized model having a further updated estimate of
model parameter uncertainties.

2.   A method according to claim 1, wherein said model of the
subsurface area has geometrical model parameters representing
geological boundaries.

3.   A method according to claim 1, wherein said model of the
subsurface area has material parameters representing
properties of distributed subsurface materials.

4.   A method according to claim 1, wherein said measurement
data comprise seismic data, drilling data, well logging data,
well test data, production history data, or permanent
monitoring data.

5.   A method according to claim 1, wherein said measurement
data and said additional measurement data comprise different
types of data.

6.   A method according to claim 5, wherein said measurement
data comprises seismic data and said additional measurement
data comprises well logging data.

7.   A method according to claim 1, wherein said
parameterized model of the subsurface area comprises a
layered model having material properties associated with each
layer.

8.   A method according to claim 1, wherein said
parameterized model of the subsurface area comprises a
geocellular model having material property values defined on
a regular or irregular three-dimensional grid.

9.   A method according to claim 1, wherein said
parameterized model of the subsurface area comprises a
geometry-based model having material property values defined
on a plurality of discrete geometrical sub-regions within the
subsurface area.

10.   A method according to claim 1, wherein said initial and
updated estimates of model parameter uncertainties comprise
probability density functions computed using deterministic
optimization or Monte Carlo sampling.

11.   A method according to claim 10, wherein said probability
density functions are multivariate normal probability density
functions definable by mean vectors and covariance matrices.

12.   A method according to claim 11, wherein a mean and
covariance matrix of said updated estimate of model parameter

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uncertainties is computed using deterministic optimization or
Monte Carlo sampling.

13.   A method according to claim 1, wherein said considering
step comprises comparing said measurement data to a model
parameter, said updating step comprises updating said
parameterized model to fit said measurement data, and said
updating step further comprising updating said initial
estimate of model parameter uncertainties to be consistent
with uncertainties associated with said measurement data.

14.   A method according to claim 1, wherein said considering
step comprising comparing said additional measurement data to
predicted data produced by a prediction algorithm operating
on said initial parameterized model.

15.   A method according to claim 1, wherein said considering
step produces a likelihood function that is combined with
said initial estimate of model parameter uncertainties to
produce said updated estimate of model parameter
uncertainties.

16.   A method according to claim 1, wherein said updating
step comprises directly updating a sample from a posterior
PDF obtained by a Monte Carlo method using said measurement
data.

17.   A method according to claim 17, wherein said updating
step comprises directly updating said sample using travel
time-depth measurement data obtained while drilling.

18.   A method according to claim 1, wherein said
parameterized model parameters may be changed during said
updating step only when said change is consistent with said
initial estimate of model parameter uncertainties.

19. A method according to claim 1, wherein any changes to
said parameterized model parameters that are inconsistent
with said initial estimate of model parameter uncertainties
are identified during said updating step.

20. An apparatus for creating a model of a subsurface area
comprising:

        means for creating a parameterized model of the
subsurface area having an initial estimate of model parameter
uncertainties;

        means for considering measurement data from the
subsurface area;

        means for updating said parameterized model to fit
said measurement data, said updated parameterized model
having an updated estimate of model parameter uncertainties;
and

        means for repeating said considering and updating
steps with additional measurement data to produce a further
updated parameterized model having a further updated estimate
of model parameter uncertainties.

21. An article of manufacture, comprising:

        a computer usable medium having a computer readable
program code means embodied therein for creating a model of a
subsurface area, the computer readable program code means in
said article of manufacture comprising:

        computer-readable program means for creating a
parameterized model of the subsurface area having an initial
estimate of model parameter uncertainties;

computer-readable program means for considering measurement data from the subsurface area;

computer-readable program means for updating said parameterized model to fit said measurement data, said updated parameterized model having an updated estimate of model parameter uncertainties; and

computer-readable program means for repeating said considering and updating steps with additional measurement data to produce a further updated parameterized model having a further updated estimate of model parameter uncertainties.
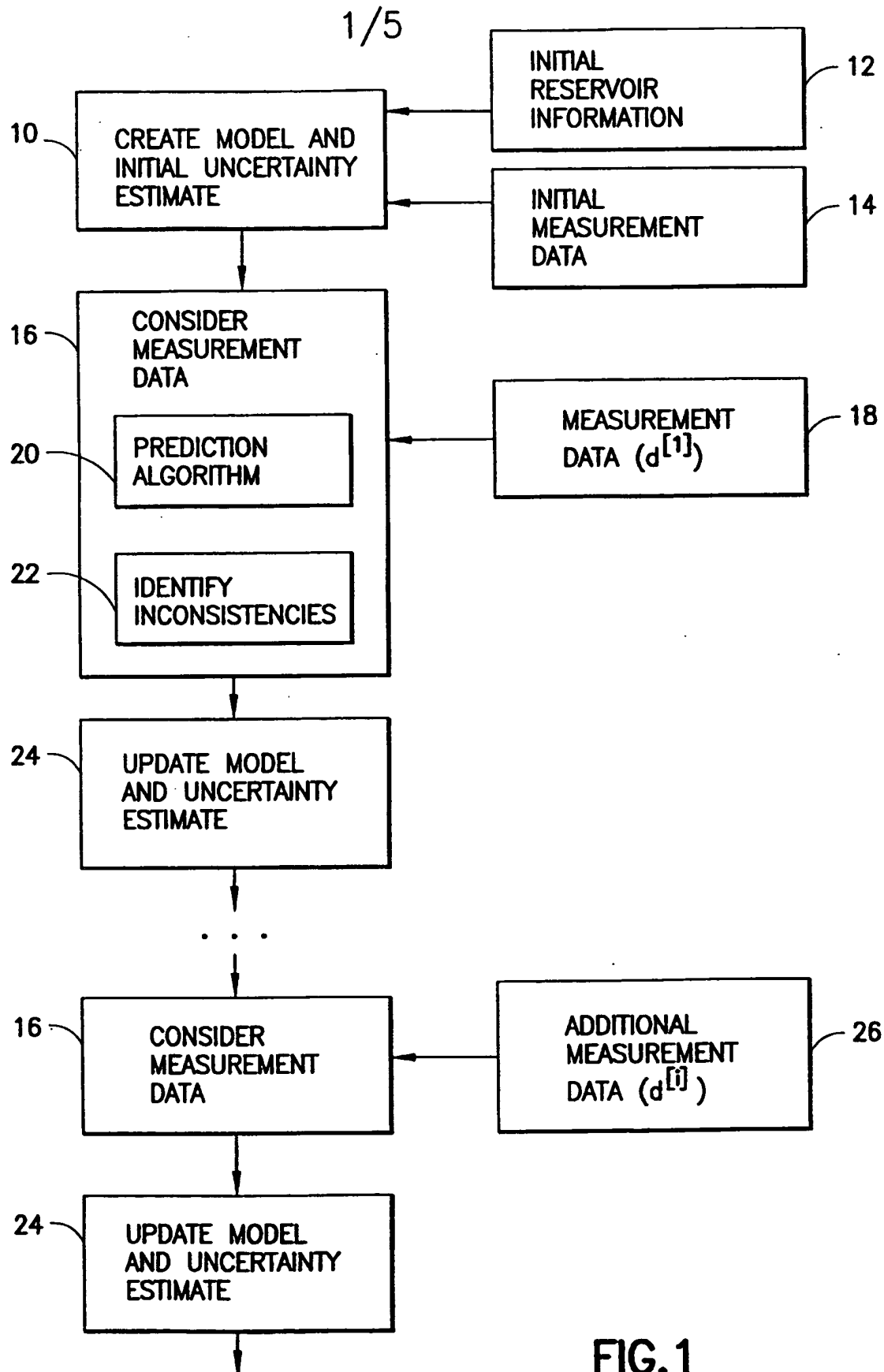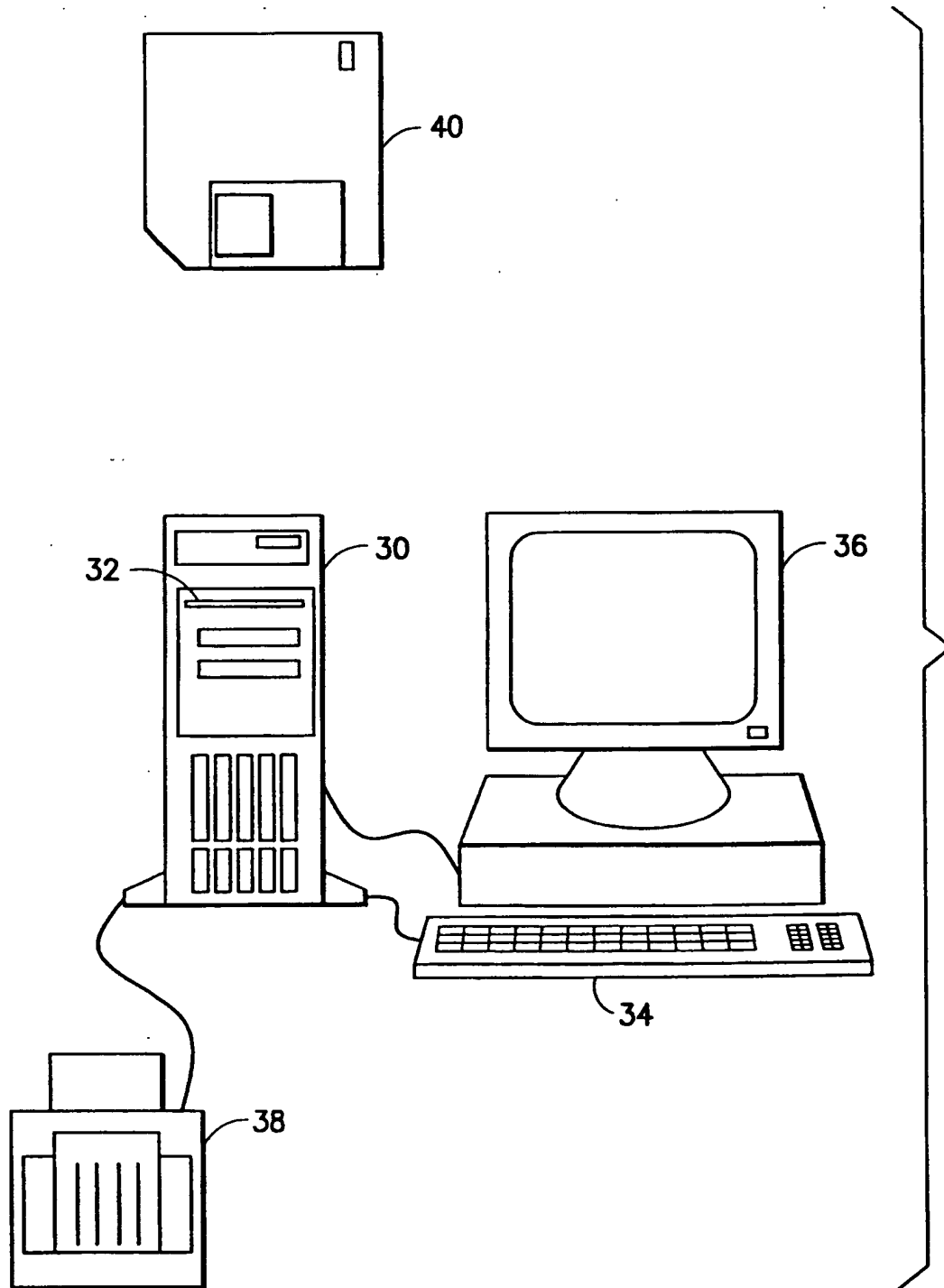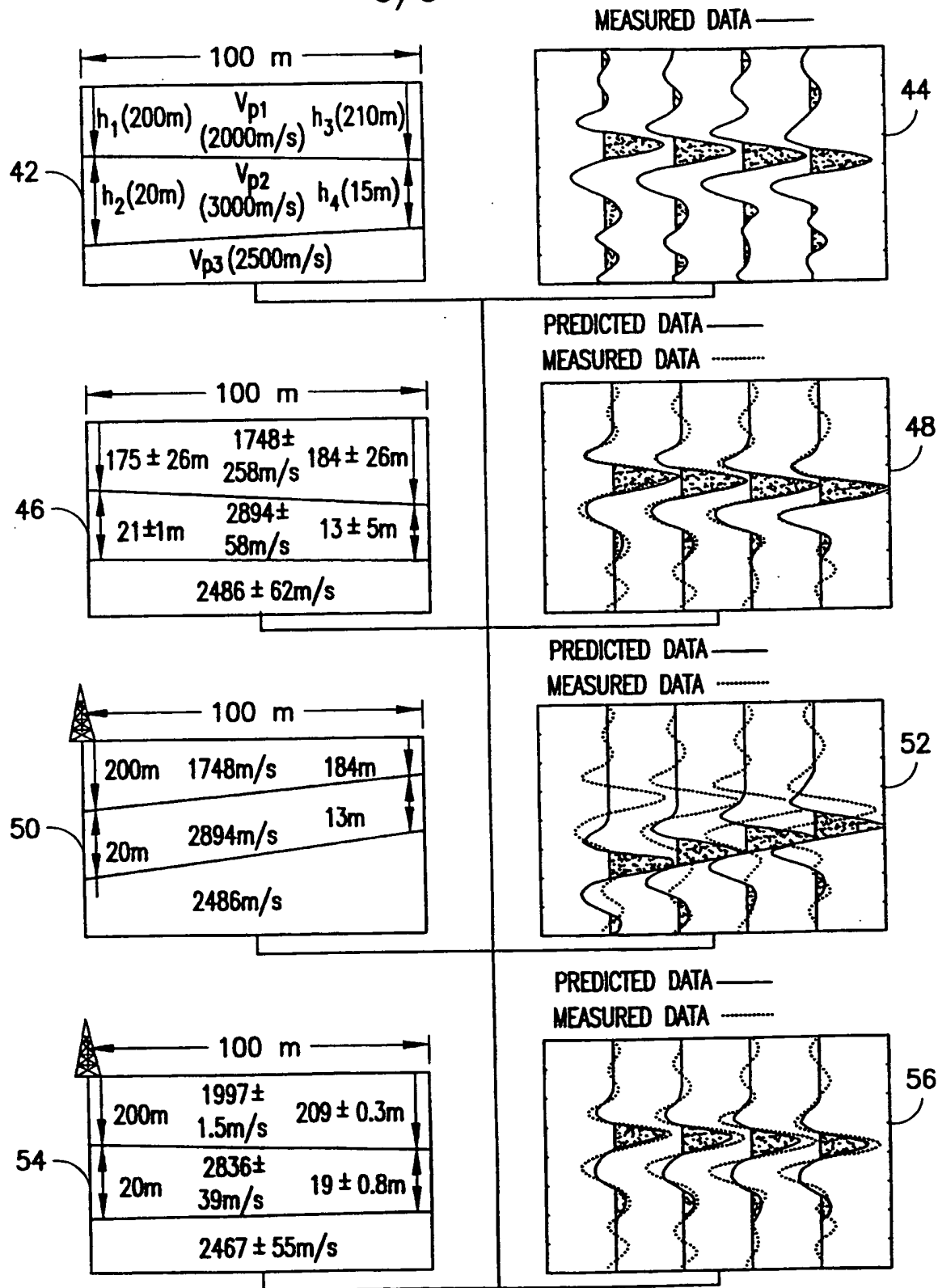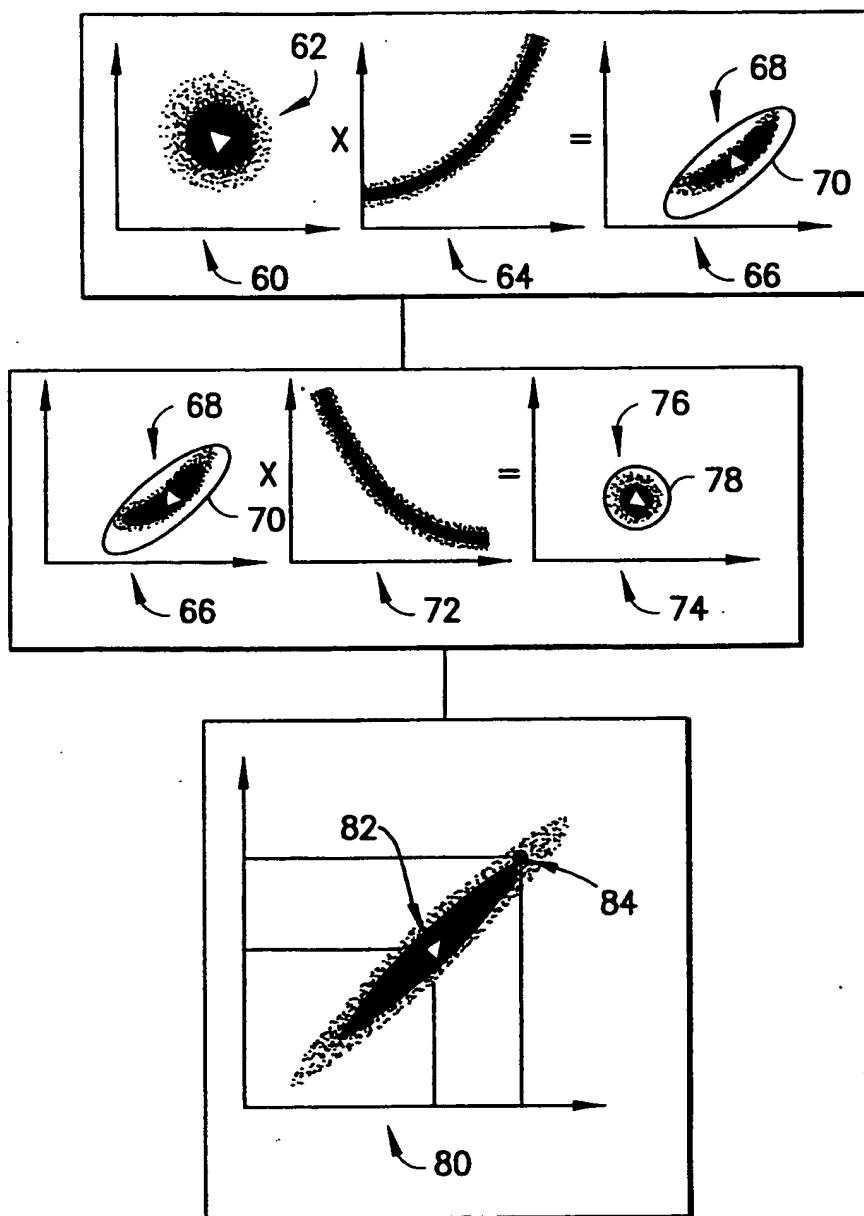
FIG.1

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FIG.2

FIG.3

FIG.4

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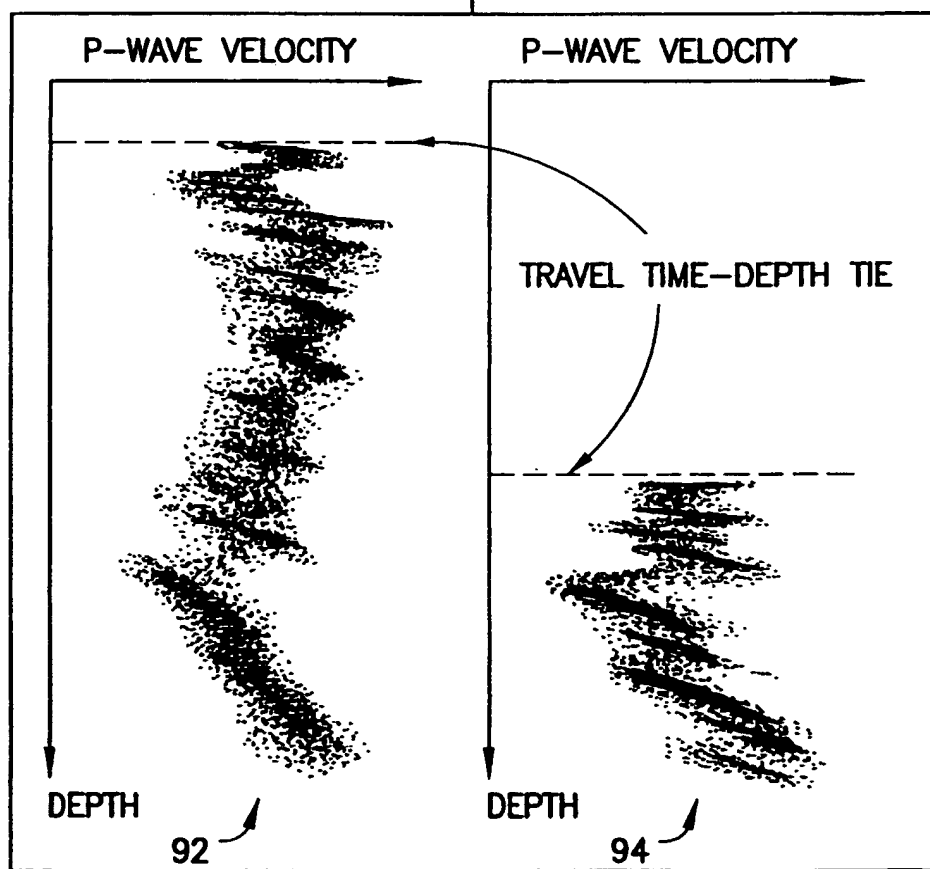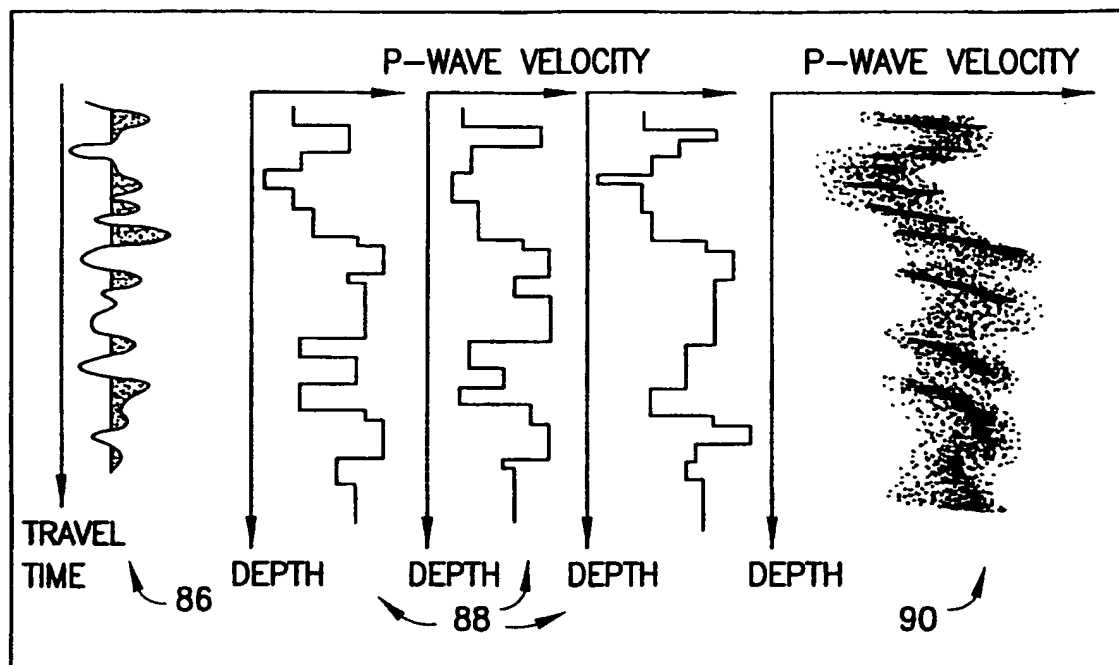
FIG.5

INTERNATIONAL SEARCH REPORT

A. CLASSIFICATION OF SUBJECT MATTER
IPC 7   G01V11/00   G01V1/28

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
IPC 7   G01V

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practical, search terms used)

EPO-Internal, WPI Data, INSPEC

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	US 5 321 613 A (VANDERGRAFT JAMES S ET AL) 14 June 1994 (1994-06-14) column 3, line 45 –column 4, line 47 column 5, line 26 –column 6, line 16	1-9,11, 13-15, 17-21
Y		10,12,16
Y	US 5 416 750 A (DOYEN PHILIPPE M ET AL) 16 May 1995 (1995-05-16) abstract	10,12,16
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[X] Further documents are listed in the continuation of box C.   [X] Patent family members are listed in annex.

* Special categories of cited documents :

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"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention

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"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
7 July 2000	17/07/2000

Name and mailing address of the ISA	Authorized officer
European Patent Office, P.B. 5818 Patentlaan 2 NL – 2280 HV Rijswijk Tel. (+31–70) 340–2040, Tx. 31 651 epo nl, Fax: (+31–70) 340–3016	Swartjes, H

INTERNATIONAL SEARCH REPORT

C.(Continuation) DOCUMENTS CONSIDERED TO BE RELEVANT

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